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Prediction of preference and effect of music on preference: a preliminary study on electroencephalography from young women

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Abstract: Neuromarketing is the application of the neuroscientific approaches to analyze and understand economically relevant behavior. In this study, the effect of loud and rhythmic music in a sample neuromarketing setup is investigated. The second aim was to develop an approach in the prediction of preference using only brain signals. In this work, 19-channel EEG signals were recorded and two experimental paradigms were implemented: no music/silence and rhythmic, loud music using a headphone, while viewing women shoes. For each 10-sec epoch, normalized power spectral density (PSD) of EEG data for six frequency bands was estimated using the Burg method. The effect of music was investigated by comparing the mean differences between music and no music groups using independent two-sample t-test. In the preference prediction part sequential forward selection, k-nearest neighbors (k-NN) and the support vector machines (SVM), and 5-fold cross-validation approaches were used. It is found that music did not affect like decision in any of the power bands, on the contrary, music affected dislike decisions for all bands with no exceptions. Furthermore, the accuracies obtained in preference prediction study were between 77.5 and 82.5% for k-NN and SVM techniques. The results of the study showed the feasibility of using EEG signals in the investigation of the music effect on purchasing behavior and the prediction of preference of an individual.

Key words: Neuromarketing, electroencephalography, decision making, normalized band powers, music effect

1. Introduction

The atmosphere that exists in a store or a restaurant have been shown to affect the preferences of individuals, while they are purchasing a product or ordering food, drink, or dessert [1–3]. The atmosphere includes the color, odor, lighting, furnishing, and sound. At some restaurants, bright lights or fast tempo music have been used to encourage rapid turnover while at some others dim light and slow music to encourage consumption of cocktails and desserts [4]. The effect of atmosphere is true not only in such stores or restaurants but also in online retailing services. The use of colors, fonts, and music might affect the consumer behavior [5–7]. In real and virtual/online settings, music is thought to be a peculiar facilitator to induce feelings and synchronously modulate underlying neurophysiological processes [8], and it is one of the tools that is used to affect the purchasing behavior of individuals.

There are different neuroscientific approaches in investigating the effect of music on the neurophysiology of the preferences such as functional magnetic resonance imaging (fMRI), positron emission tomography (PET),

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electroencephalography (EEG), magnetoencephalography (MEG), steady-state topography (SST), galvanic skin response (GSR), and several other physiological parameters [9–11]. It is known that marketing research is fundamentally about understanding, explaining, and predicting purchase behavior of individuals and the term neuromarketing has been used to mean the application of the neuroscientific approaches to analyze and understand economically and commercially relevant behaviors [12, 13]. Additionally, several recent studies showed that the number of neuromarketing studies are increasing each year [14–16].

In the analysis of preferences of individuals related to commercial purposes, and the effect of music on this behavior, multichannel EEG that provides spatio-temporal information about the dynamics of brain with a high temporal resolution has been frequently used [9–11, 17–19]. In a recent study, Lin et al. [20] classified emotional states like joy, anger, sadness, and pleasure from EEG signals while listening to music. In another study, Wang et al. [21] proposed an EEG-based classification system for four emotional states using movie stimuli with alpha and gamma power-band features.

In EEG-based neuromarketing research, a common practice is to use clips of ads, pictures of commercial goods or brand logos, and jingles as visual or audio stimuli. Usually, one of the aims of this kind of research is to investigate the relationship between features extracted from EEG signals during such stimuli and self-reported feelings or decisions during or after the stimuli [22]. It is arguable that the prediction of preference without self-reporting might open new doors in neuromarketing research, but this study used self-reporting decisions for further analysis.

In a previous study, using multichannel EEG, we investigated the neurophysiological manifestations of like and dislike decisions using women's shoes as visual stimuli in a silent environment on male and female subjects. We searched for the frequencies and electrode positions that could be used in the discrimination of like and dislike decisions. In the present study, we investigated two arguments using multichannel EEG recorded from young female college students: 1) Does rhythmic and loud music affect the preferences (i.e. like or dislike decisions) significantly? 2) Is prediction of a preference while viewing a picture of a commercial good (women's shoes) possible with a reasonable accuracy using only the features extracted from EEG signals?

2. Materials and methods

2.1. Study population and data acquisition

For this study, ten right-handed female college students (ages between 19 and 24) with no previously known neurological diseases were recruited. All subjects agreed to sign an informed consent before the experiments.

We recorded 21 channels of EEG signals according to international 10-20 system [18] and 19 of these channels were used in our analysis. The data acquisition system was EEG 1200 (Nihon Kohden Co., Tokyo, Japan) that allowed pressing a timing marker button for time referencing. Electrode locations were cleaned with alcohol patches before connecting the electrodes in order to increase signal quality. The recordings were unipolar with reference to the ear electrodes positioned on the side of the earlobe.

Figure shows the flow of the study. During the data acquisition sessions, subjects sat in a chair, which was 1 m away from a 15-inch monitor and they were looking at a full-screen, high-quality shoe photographs. 16 different women's shoe photographs, which were saved from a web site of a company, were presented during the experiment. The slide show of the experiment was time-adjusted in such a way that for the first 5 s of slide only blank screen was shown, a shoe photograph was then shown for 10 s. This procedure was repeated for all 16 shoes. EEG data acquiring started once the subject was ready which was before the slide show. The supervisor of the experiment placed a time marker (from the keyboard) on the data synchronously with the onset of the slide show without disturbing the subject. The subjects pressed the time marker button, when they liked the shoe that was shown on the screen and did nothing when they did not like it.

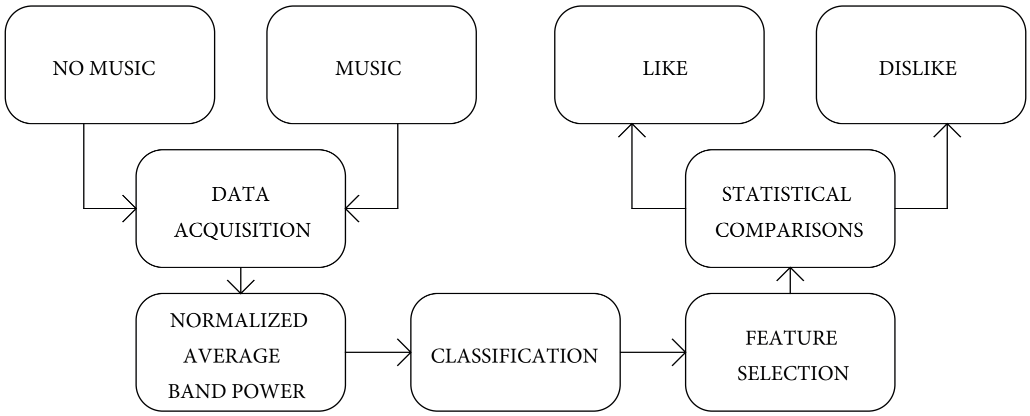

Figure. The flow of the study from data acquisition to final analysis.

In this study there were two paradigms: no music during data acquisition and data acquisition while listening to rhythmic and loud music (Lady Gaga, Poker Face, sampling rate: 22,050 Hz) using a headphone with high sound quality. These two paradigms are referred to as “no-music” and “music” in this manuscript. The shoe designs used in the no-music and music paradigms were similar to each other. This experimental approach worked as a test bed for investigating the effect of music on the preference mechanism.

The sampling rate of EEG recordings was 500 samples/seconds and analog to digital (A/D) conversion resolution was 16 bits. For each subject, 4-min-long data (16 shoes x 15-s recordings) was recorded from 19 channels. The recorded multichannel EEG data were converted into *.mat* files for processing in MATLAB software (Matlab R2011b, The MathWorks Inc., Natick, MA, USA).

2.2. Data preprocessing

The preprocessing step of this study included initial filtering, removing 5 s background/plain slides, removing noisy EEG signal portions and composing final dataset with sufficient length. These steps were applied on the multichannel EEG records coming from both no-music and music paradigms. Each 4-min data recorded from each channel was first filtered using a 100th degree window-based linear-phase finite impulse response digital band-pass filter (FIR1 in MATLAB). The cut-off frequencies of this filter were 1 and 45 Hz. In order to circumvent the phase shift in the data introduced by this filter, the built-in filtfilt function was employed. In order to focus on 10-s epochs that correspond to like/dislike decisions, we removed initial 5-s portions (plain slides) that corresponded to resting state of the recordings. This 10-s data were processed, using custom-developed user interface of the system and the starting and ending points of each noisy portion (due to eye blinking or eye movement) of the data was determined and cropped. Thus, clean EEG dataset was obtained, which contained only brain activity signals acquired during shoe presentation phase of the experiment. If the length of the clean signal was smaller than 4.6 s (2300 samples), these epochs were left out of the analysis.

2.3. Normalized average band power

Using the Burg method [23], the power spectral density of each clean epoch was estimated for each subject. This method is a parametric spectral estimation approach that is based on autoregressive (AR) prediction model. The model order was assigned as 15 according to [24]. This approach first resolves closely spaced sinusoids in signals with low noise levels, and second, successfully estimates power spectral densities of short data recordings and assures a stable AR model. Finally, it is a computationally efficient approach [25].

From each clean epoch of the data, the spectral coefficients at every half Hz between 1 to 45 Hz (f = 1, 1.5, 2, 2.5, 3 … 44, 44.5, 45 Hz) total of 91 frequency points were estimated. Out of these frequencies normalized average band powers were calculated. The used bands were theta (3.5–7.5 Hz), alpha (8–13 Hz), beta_low (13.5–22 Hz), beta_high (22.5–30 Hz), gamma_low (30.5–38 Hz), and gamma_high (38.5–45 Hz) bands. The average band power was computed by taking the mean of the coefficients in the corresponding band. The coefficients were then normalized by dividing the average power by the variance of the total signal in order to minimize intersubject and intrasubject variability. For each epoch, 6 normalized average band power values were obtained, and these values were computed for all 19 channels separately.

2.4. Statistical analysis: no music vs music

During the experiments, when the subjects liked the presented shoe, they pressed on the timing button as it was mentioned before. From this action, two types of information were extracted: the timing of the like decision and the shoe number liked by the subject. In the first step of the analysis, the numbers and the timings of like decisions during music and no-music experimental paradigms were compared. In the second step, two datasets of normalized average band power (NABP) values were formed from six spectral bands mentioned above. These four datasets were compiled using all NABP values from 6 bands and 19 channels coming from like cases (the shoes that the subjects liked) and dislike cases (the shoes that the subjects did not like), when the subjects listened to loud and rhythmic music (music paradigm, like and dislike datasets) and did not listen to any music at all (no-music paradigm, like and dislike datasets). From the values that are coming from each band of all channels under two different experimental paradigms, it was possible to investigate the effect of music in like and dislike decisions for each band. For statistical analysis, SPSS 18.0 software package (IBM, Armonk, NY, USA) was used and the mean differences between four different states were evaluated using independent two-sample t-test for each band. These four states were like and dislike decisions with and without music (like with music, dislike with music, like without music, dislike without music). Our hypothesis for each band (theta to gamma_high bands) was that music did not affect the like or dislike decisions. The statistical significance level was $P < 0.05$.

2.5. Prediction of decision

In the second part of the study, the aim was to investigate the feasibility of using pattern-classification approaches for the prediction of a like/dislike decision using only the band power values from 19 EEG channels. The classification study was performed on music and no-music paradigms separately in order to compare both their prediction accuracies and the selected channels and bands in the associated paradigm.

The classification approaches used were the k-nearest neighbors (k-NN) approach [26] and the support vector machines (SVM) [27]. For each paradigm, the associated dataset was divided into 5 portions, 4 of which were used as the training set and the remaining as the test set. In both classification approaches, the samples were multi-dimensional NABP values from 19 channels and labeled as like or dislike accordingly. In the training phase of the k-NN approach, a feature vector coming from the training set corresponding to one shoe presentation was assigned to the class that was the most frequently encountered among the k-nearest samples (k = 3) using the Euclidean distance. After the training phase, a feature vector coming from the test set was categorized as like or dislike by assigning it to the class of the most frequently seen neighbors among the k-training samples nearest to that vector. To find the overall prediction accuracy rate, this procedure was repeated for 5 times, each portion of the dataset served as the test set for each iteration. This approach is called the 5-fold cross-validation technique. The SVM approach is a representation of the training feature vectors as points in space mapped so that the vectors of different classes are separated by a well-defined gap that is as wide as possible. Using the test data, the vectors are projected on that same space and estimated to be the member of a class according to the side of the gap they fall on. In the classification part of this study, there were like and dislike classes and the SVM method was executed with the radial basis function (RBF) kernel.

In the feature selection part of the study, in which the best subset representing the original feature set is chosen, ten features were selected to be used in the classification phase such that each feature belonged to a different band from a different channel. The sequential forward selection (SFS) approach was the method of choice, because it is easy to implement and offers relatively good performance [27]. In this method, the 'selected features set' was started with a vacant set; the feature resulting in the highest accuracy in terms of correct classification of preferences was added to the 'selected features set'. The remaining features were then sequentially added to the selected feature set and the combination of features resulting in the highest performance became the new selected features set and so on. This feature selection process was continued until ten features were selected. The number of features with the best accuracy was noted for each method and paradigm. If it was less than ten features, that value was reported as the number of features with the best accuracy.

3. Results

3.1. Effect of music on preference

As shown in Table 1, the number of like decisions was very similar and it was 49 and 48 out of 160 decisions. The average like decision timings were 2.35 (SD 2.05) and 2.375 (SD 1.82) s for music and no-music paradigms, respectively. The mean differences between the two paradigms were evaluated using independent two-sample t-test, and no statistical significance was found with a confidence level of 95%.

The preprocessing step of this study included the manual removal of artifacts like blinking or other muscle artifacts using a custom MATLAB-based graphical user interface as it was mentioned before. If the length of the data in each 10 s epoch (shoe slide presentation) was less than 4.6 s after the noise removal process, that epoch was excluded and it was not used in further analysis. There were 34 epochs out of 49 like decision recordings and 86 epochs out of 111 dislike decision recordings in the music paradigm, which were clean enough for the further analysis. On the other hand, in the no-music paradigm all like decision recordings and 105 out of 112 dislike recordings were clean enough for further analysis. It was evident that the EEG recordings contained more noisy parts in the music paradigm than the no-music paradigm.

In the statistical analysis with respect to the effect of music on like or dislike decision, the mean differences between each band of like decisions with music and no-music paradigms, and each band of dislike decisions with music and no-music paradigms were investigated. The hypothesis was that music did not affect the like or dislike decisions of individuals for each band level. Table 2 and 3 depict group statistics for normalized band

Table 1. The statistics on like decisions for each subject and experimental paradigm.

Subject no.	Music		No-music	
	Number of likes	Like decision timing (s)	Number of likes	Like decision timing (s)
1	4	Mean: 3.75 Range: 1–8	5	Mean: 2.4 Range: 1–4
2	10	Mean: 1.1 Range: 1–2	12	Mean: 1.2 Range: 1–2
3	3	Mean: 2.33 Range: 2–3	2	Mean: 2 Range: 1–3
4	6	Mean: 3.0 Range: 2–4	5	Mean: 3.2 Range: 2–8
5	7	Mean: 1.4 Range: 1–3	7	Mean: 3.7 Range: 1–8
6	3	Mean: 4.66 Range: 2–6	1	Mean: 0 Range: 0–0
7	4	Mean: 3.75 Range: 2–8	4	Mean: 2.50 Range: 1–5
8	5	Mean: 3.0 Range: 1–6	5	Mean: 4.8 Range: 2–9
9	1	Mean: 2.0 Range: 2–2	3	Mean: 1.66 Range: 1–2
10	6	Mean: 1.0 Range: 1–1	4	Mean: 1.0 Range: 1–1

Table 2. Group statistics for the comparison of like decisions for music and no-music paradigms.

	Paradigm	N	Mean	SD
Theta	Music	646	0.194	0.202
	No-music	912	0.183	0.221
Alpha	Music	646	0.178	0.203
	No-music	912	0.177	0.219
Beta_low	Music	646	0.159	0.200
	No-music	912	0.158	0.212
Beta_high	Music	646	0.135	0.183
	No-music	912	0.129	0.188
Gamma_low	Music	646	0.140	0.180
	No-music	912	0.129	0.190
Gamma_high	Music	646	0.117	0.160
	No-music	912	0.117	0.183

N is 646 (34 x 19) for music and 912 (48 x 19) for no music cases. SD: standard deviation. SD: standard deviation.

Table 3. Group statistics for the comparison of dislike decisions for music and no-music paradigms. N is 1634 (86x19) for music and 1995 (105x19) for no-music cases.

	Paradigm	N	Mean	Std
Theta	Music	1634	0.184	0.197
	No-music	1995	0.141	0.167
Alpha	Music	1634	0.164	0.181
	No-music	1995	0.143	0.171
Beta_low	Music	1634	0.140	0.167
	No-music	1995	0.113	0.151
Beta_high	Music	1634	0.131	0.173
	No-music	1995	0.108	0.154
Gamma_low	Music	1634	0.135	0.168
	No-music	1995	0.111	0.150
Gamma_high	Music	1634	0.124	0.170
	No-music	1995	0.099	0.146

Table 4. Independent samples test results for like and dislike decisions for each band.

	LIKE	DISLIKE
	Sig. (p)	Sig. (p)
Theta	0.297	0.000
Alpha	0.917	0.000
Beta_low	0.924	0.001
Beta_high	0.576	0.000
Gamma_low	0.276	0.000
Gamma_high	0.987	0.000

power values of like and dislike decisions, respectively. The mean and standard deviation values were computed using all channels.

In Table 4, the statistical comparison results are demonstrated. In this part, it was found with 95% confidence that music did not affect like decision in any of the power bands (p values were greater than 0.05), on the contrary, music affected dislike decisions for all bands with no exceptions.

3.2. Prediction of preference

In the final part of this study, using feature selection and classification approaches, the potential of predicting like or dislike decision from only multichannel EEG data was investigated. The k-NN classification approach resulted in 82.5% accuracy with 8 and 7 selected features for both music and no-music paradigms, respectively. The selected 8 channels and bands (in parenthesis) for k-NN evaluation of music paradigm are the following:

- C4-A2 (Theta, Alpha), F7-A1 (Gamma_low), F8-A2 (Alpha, Beta_high, Gamma_high), T6-A2 (Gamma_high), T5-A1 (Beta_high).

The selected 7 channels and bands for k-NN evaluation of no-music paradigm are the following:

- C4-A2 (Gamma_low, Beta_low), Pz-A1 (Beta_low), F3-A1 (Theta), P4-A2 (Beta_low), T5-A1 (Theta), C3-A1 (Alpha).

When SVM was chosen as the classification approach, the accuracy of decision prediction was found to be 77.1% and 77.5% with 4 and 7 selected features for music and no-music paradigms respectively. The selected 4 channels and bands for SVM evaluation of music paradigm are the following:

- O1-A1 (Beta_high, Alpha), Pz-A1 (Gamma_high), P4-A2 (Gamma_high).

The selected 7 channels and bands for SVM evaluation of no-music paradigm are the following:

- T4-A2 (Gamma_high, Beta_high), Cz-A1 (Alpha), F3-A1 (Gamma_high), F7-A1 (Beta_high), O1-A1 (Gamma_low, Theta).

4. Discussion and conclusion

The aims of this study were two-fold: investigation of the effect of loud and rhythmic music on the subjects' preferences (like or dislike decision) and feasibility of prediction of preferences using multichannel EEG signals and pattern recognition approaches. Our case study involved testing the partiality of 10 female subjects with women's shoes without music and with music paradigms. The summary of our key findings is as follows:

- The mean of like decision duration and the number of like decisions were very similar for music and no-music testing paradigms, which denotes that loud and rhythmic music did not have notable effect on the like decisions for these subjects. In both cases, with and without music, approximately one-third of the whole shoe-image set was liked.

- Even though different shoe-image sets were used in different testing paradigms, the outcome of this study showed that they were successfully matched.

- The mean and standard deviation values for each frequency band were higher in music paradigm than they were in no-music paradigm, which means the normalized band power values increased with music.

- An interesting finding was that the dislike decisions were significantly different with music paradigm compared to the no-music paradigm, which means loud and rhythmic music have effect on dislike decisions.

- The prediction accuracies for different classification approaches were also quite similar and ranged between 77.5 and 82.5%, which means four out of five decisions could be predicted using less than eight channels. In addition, prediction accuracy performances were not affected by occurrence of music during EEG records, which means that presence of auditory stimuli did not have distinctive effect on EEG signals of like and dislike decisions.

- For different channels, alpha, beta_high, and gamma_high bands were the most frequently selected bands that were used in further analysis.

- No selected channel-band combinations were common in both classification methodologies and testing paradigms, which means that the selected channel-band combination was highly dependent on the paradigm and methodology.

- For k-NN, half of the selected bands came from the channels on the left hemisphere, but C4-A2 seemed to be a significant channel for both music and no-music paradigms.

It is evident that in marketing research the evaluations rely entirely on the skill and eagerness of the individual to correctly report their decisions and partialities [28]. Therefore, assessment of neurophysiological correlates of consumer behavior has triggered substantial interest within the marketing profession [29]. The advantages of neurophysiological measurement for this purpose have been prominent for at least 30 years [30].

In [31], it was claimed that music is an important component of the servicescape and it affects customers' feelings and moods. In various other studies, researchers investigated the influence of background music on the physical or virtual environments [2–4, 7, 32–35].

In one of the studies investigating the relationship between music and brain waves, Bhattacharya et al. [36] worked with musicians and nonmusicians on the correlation of gamma waves and music perception. In another study, Koelsch and Mulder [37] recorded EEG signals, while listening to Mozart, Haydn, Schubert, and Beethoven sonatas. A thesis study discovered that F7, F3, Cz, T3, are T4 channels are very sensitive to music [38]. In addition, in [39], it was found that the alpha wave can be used as an index for pleasure stimulated by music and two frontal channels (Fp1 and F7) can be used to observe the auditory response to pleasurable music.

Although the results and findings of this study are exciting, it is evident that these findings need validation with studies with a larger subject size, from different ages, and with different types of music with different amplitude, tempo, and rhythm. One of the limitations of this study was that it was performed only on 10 young female volunteers and one type of visual stimulus, women's shoe. The visual stimulus can also be varied in future studies.

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